Title
Parameter sensitivity analysis for different complexity land surface models using multicriteria methods

Journal
Journal of Geophysical Research Atmospheres, 111(20)

ISSN
0148-0227

Authors
Bastidas, LA
Hogue, TS
Sorooshian, S
et al.

Publication Date
2006-10-27

DOI
10.1029/2005JD006377

Parameter sensitivity analysis for different complexity land surface models using multicriteria methods

L. A. Bastidas,[1] T. S. Hogue,[2] S. Sorooshian,[3,4] H. V. Gupta,[5,6]
and W. J. Shuttleworth,[5,6]

Received 15 June 2005; revised 22 March 2006; accepted 7 June 2006; published 17 October 2006.

[1] A multicriteria algorithm, the MultiObjective Generalized Sensitivity Analysis (MOGSA), was used to investigate the parameter sensitivity of five different land surface models with increasing levels of complexity in the physical representation of the vegetation (BUCKET, CHASM, BATS 1, Noah, and BATS 2) at five different sites representing crop land/pasture, grassland, rain forest, cropland, and semidesert areas. The methodology allows for the inclusion of parameter interaction and does not require assumptions of independence between parameters, while at the same time allowing for the ranking of several single-criterion and a global multicriteria sensitivity indices. The analysis required on the order of 50 thousand model runs. The results confirm that parameters with similar ‘‘physical meaning’’ across different model structures behave in different ways depending on the model and the locations. It is also shown that after a certain level an increase in model structure complexity does not necessarily lead to better parameter identifiability, i.e., higher sensitivity, and that a certain level of overparameterization is observed. For the case of the BATS 1 and BATS 2 models, with essentially the same model structure but a more sophisticated vegetation model, paradoxically, the effect on parameter sensitivity is mainly reflected in the sensitivity of the soil-related parameters.

Citation: Bastidas, L. A., T. S. Hogue, S. Sorooshian, H. V. Gupta, and W. J. Shuttleworth (2006), Parameter sensitivity analysis for different complexity land surface models using multicriteria methods, *J. Geophys. Res.*, *111*, D20101, doi:10.1029/2005JD006377.

1. Introduction and Scope

[2] This paper discusses the utility of applying multicriteria methods to sensitivity analysis in order to evaluate and improve the ability of different complexity land surface models (LSMs) to simulate the turbulent heat and water exchanges, and the temperature and water content of the soil. Five models, each having different degrees of complexity in the representation of the soil and vegetation processes, are used in conjunction with observational data collected at five different sites around the world. One of these data sets (Cabauw data set) has already been used extensively for the Project for Intercomparison of Land-Surface Parameterization Scheme (PILPS) 2 studies [e.g., *Henderson-Sellers et al.*, 1995; *Desborough*, 1999]. The other data sets have been used by other investigators [e.g., *Unland et al.*, 1996; *Bastidas et al.*, 1999; *Gupta et al.*, 1999; *Sen et al.*, 2001; *Hogue et al.*, 2005].

[3] The sensitivity analysis (SA) procedures are carried out within a multicriteria framework using an algorithm originally developed for application to LSMs, i.e., the MultiObjective Generalized Sensitivity Analysis (MOGSA) algorithm [*Bastidas et al.*, 1999]. We investigate and compare the influence of different climatic regimes and vegetation biomes on the parameter behavior and in particular how the model structure affects the sensitivity of parameters with the same physical meaning.

[4] The goals of the present study are (1) identify the sensitivity of the numerous parameters in commonly used LSMs; (2) determine whether the number of sensitive parameters changes as model complexity (in the present study we use the number of parameters as a proxy for the model complexity) increases; and (3) study how different parameterizations affect the sensitivity of parameters with similar physical meaning under different environmental conditions, i.e. variation from site to site.

[5] This paper is organized as follows: section 2 discusses the background and context for this work and presents a review of the literature. Section 3 briefly describes the data sites and models used. In section 4, the multicriteria framework for sensitivity analysis and the MOGSA algorithm are

[1]Department of Civil and Environmental Engineering and Utah Water Research Laboratory, Utah State University, Logan, Utah, USA.
[2]Department of Civil and Environmental Engineering, University of California, Los Angeles, California, USA.
[3]Center for Hydrometeorology and Remote Sensing, University of California, Irvine, California, USA.
[4]Also at Department of Civil and Environmental Engineering, University of California, Irvine, California, USA.
[5]Department of Hydrology and Water Resources, University of Arizona, Tucson, Arizona, USA.
[6]Also at NSF Science and Technology Center for Sustainability of Semi-Arid Hydrology and Riparian Areas (SAHRA), University of Arizona, Tucson, Arizona, USA.

0148-0227/06/2005JD006377

described. Section 5 discusses the results of the analysis. Section 6 contains conclusions and future extensions.

2. Background

[6] Currently a large number of LSMs are in use (in excess of 30). This fact stimulated the PILPS [e.g., *Henderson-Sellers and Brown*, 1992; *Henderson-Sellers et al.*, 1995; *Pitman and Henderson-Sellers*, 1998; *Boone et al.*, 2001; *Nijssen et al.*, 2003]. Excellent overviews of the different existing LSMs and their evolution are given by *Pitman* [2003] and *Viterbo* [2002]. However, few LSMs have been subject to calibration/parameter estimation and sensitivity analysis procedures because, as *Beck* [2002] remarks, in the context of environmental models, it has often been considered that models requiring calibration against observations are inferior and incapable of extrapolation to describe conditions not previously observed. The preferable alternative, it has been believed, is to develop models based on the laws of physics that employ constants whose values are known a priori and are universally applicable, independent of the specific model equations used (originally PILPS assumed this). Ideally they will only contain parameters having physical meaning that were amenable to independent measurement in the field and whose behavior will be independent of the forcings and the parameterizations. As a result, such models would be expected not to require calibration. However, such a happy state of affairs does not prevail in practice: to believe so would appear to be an illusion, albeit a useful one [*Beck*, 2002]. Of course, in some cases, it may be possible to directly obtain estimates of certain model parameters from measurements at field sites or via remote sensing data. Such parameters could be considered physical parameters–examples might include vegetation cover, slope, leaf area index, vegetation height, etc. On the other hand, many model parameters in the models may not be obtainable from direct measurements, in which case, some other method must be used to find appropriate values. Such parameters could be considered "functional" or effective parameters [*Sorooshian and Gupta*, 1995]–examples might include soil diffusivity, soil thermal capacity, and hydraulic conductivity, among others. It is, therefore, important to assess the effect that these functional parameters can have on the model response and how that influence varies with the model complexity and the forcings.

[7] Although sensitivity analysis has been used widely in systems and reliability engineering, it has seen less use in the physical and natural sciences [*Saltelli*, 1999]. A robust and reliable sensitivity analysis is a valuable tool in verifying the response of the model to its input parameters and assigning uncertainty to these inputs. If the input-state-output response of a model is insensitive to a parameter, it may be appropriate to use an a priori or default value for the simulations. However, if the input-state-output response is sensitive to specification of the parameter value, it is essential to adjust the parameter so that model responses are constrained to closely match available observations [*Gupta et al.*, 1999]. A crucial step in the modeling process is, therefore, to first identify which parameters within the model are sensitive (to each landcover type) and then to further adjust or calibrate these parameters in a reliable, objective manner.

[8] Furthermore, *Saltelli* [2000], quoting *Rabitz* [1989], states that to perform modeling without SA is intellectually dishonest and that all models should undergo sensitivity analysis as a matter of course prior to and during their use in different applications. SA is a fundamental ingredient for model building and a key tool in the understanding of complex physical processes. In the work reported here, we use the SA to both do this, and also to reduce the dimensionality of the parameter estimation problem [*Bastidas et al.*, 1999; *Hornberger et al.*, 1985; *Rabitz and Alis*, 2000], this being a critical issue when dealing with such complex models such as LSMs.

[9] *Saltelli* [1999], in his critique of common SA methods, stated that current techniques are often improperly used, especially OAT (one factor at a time) methods, which are used to draw conclusions regarding the impact of variable input factors on the prediction of the model. To adequately assess model sensitivity and to discriminate between models, concurrent variation of the entire input space must be explored [*Saltelli*, 1999]. OAT methods have been common within the land surface community [e.g., *Wilson et al.*, 1987a, 1987b; *Pitman*, 1994; *Gao et al.*, 1996]. Improved methods recently used by the land surface community include factorial methods [e.g., *Henderson-Sellers and Brown*, 1992; *Lettenmaier et al.*, 1996; *Liang and Guo*, 2003], the Fourier amplitude sensitivity test (FAST) [*Collins and Avisssar*, 1994], and the regionalized sensitivity analysis (RSA) methodology [*Franks and Beven*, 1997]. However, these methods assume model parameter independence (excluding the factorial method) and are also computationally unreasonable for models with large numbers of parameters [*Bastidas et al.*, 1999; *Liang and Guo*, 2003]. In addition, very few of the reports based on these methods have employed real system data or use extended time periods for analysis. A multiobjective, system-based approach that accounts for the interaction and interdependence of parameters was proposed by *Bastidas et al.* [1999]. The MultiObjective Generalized Sensitivity Analysis (MOGSA) was applied to the BATS land surface model (version 1e) using data from two specific study sites (ARM-CART and Tucson, Arizona); it was also applied to the Simple Biosphere Model 2 (SiB2) at a single location in the Amazon Forest near the city of Santarem in Brazil to evaluate the changes between prelogged and logged forest simulations (L. A. Bastidas et al., Influence of selective logging in the Amazon on SiB2 parameter values using multi-criteria methods, submitted to *Journal of Geophysical Research*, 2005).

[10] The MOGSA algorithm has also been applied to the SiSPAT-RS [*Braud et al.*, 1995] model at a French site near Avignon [*Demarty et al.*, 2004] not only to examine the sensitivity of the parameters but also to determine a meaningful range of parameter values. These studies have demonstrated that the algorithm is capable of effectively identifying sensitive parameters specific to the study sites.

[11] The comparisons between land surface models (LSM) have been an ongoing effort for more than a decade. PILPS has been a major venue for these efforts since it was launched in 1992 by the WMO-CAS Working Group on Numerical Experimentation (WGNE) and now in the Sci-

Table 1. Site Characteristics

Site	Latitude	Longitude	Altitude, m.a.s.l.	Vegetation Type	Average Precip., mm/yr	Average Temp., °C	Data Period
ARM-CART E13	36.605°N	97.485°W	318	flat cattle pasture	785	15.3	Apr–Aug 1995
Cabauw	51.966°N	4.933°W	−0.7	grass field	793	9.8	Jan–Dec 1987
Illinois	40.000°N	88.283°W	300	rotating crop	951	10.8	Jan–Dec 1998
Reserva Jaru	10.083°N	61.917°W	120	tropical rain forest	2300	25.1	May 1992 to Dec 1993
Tucson	32.217°N	111.083°W	730	semiarid desert	305	20.2	May 1993 to Apr 1994

ence Panel of the GEWEX Global Land Atmosphere System Studies (GLASS) [e.g., *Henderson-Sellers and Brown*, 1992; *Henderson-Sellers et al.*, 1995; *Pitman and Henderson-Sellers*, 1998; *Pitman et al.*, 1999]. In particular, phase 2 of the PILPS has been devoted to the comparison of LSM models in an offline mode, using observed meteorological forcings to drive the models. Comparisons made to date have been based mostly on time-aggregated measures to check for the energy balance [*Henderson-Sellers et al.*, 1995] or to match the monthly streamflow observations of continental-scale watersheds [*Lettenmaier et al.*, 1996; *Schlosser et al.*, 2000; *Boone et al.*, 2001; *Nijssen et al.*, 2003]. The current study attempts to look at the model performance at high frequencies, i.e., at the 20 or 30 minute time step of the observations.

3. Data Sites and Models

3.1. Sites

[12] Data collected at five field sites were used in this study. The sites were chosen on the basis of the data availability and to represent varying environments and vegetation characteristics. Specifically, the sites considered were the ARM-CART E13 field site in Oklahoma, USA; the ABRACOS Reserva Jaru field site in Ji-Parana, Brazil; the CABAUW field site in the Netherlands; an Ameri-Flux site in Illinois, USA; and a semiarid field site near Tucson, Arizona, USA. These sites may be considered representative of agricultural cropland/pasture, tropical rain forest, grassland, cropland, and semiarid biomes, respectively. A listing of these sites giving respective details, including annual precipitation, temperature, and global locations appears in Table 1.

[13] To achieve the required continuous set of forcing data, synthetic data were generated to fill gaps. For periods of missing data lasting two hours or less, intermediate values were generated by linear interpolation. If the period was longer than two hours, the appropriate hourly average value for the month in which the data gap occurred was used, except for the ARM-CART site, where data from a nearby data location were used. A quality check was performed on all the data sets to screen out obviously spurious values from the observations. For measurements made using Bowen ratio systems, values of fluxes obtained when the Bowen ratio was close to one were also discarded.

[14] At all sites we have used sensible heat, latent heat, and ground temperature as the variables of study together with the root mean square error as the single criterion objective function.

3.1.1. ABRACOS Field Site (Reserva Jaru)

[15] The tropical rain forest data were collected at the Reserva Jaru forest site (10°5′S, 61°55′W, altitude 120 m), 80 km northeast of Ji-Parana in Rondonia, close to the southwestern edge of the Amazon forest in Brazil. The wet season is December through April, and there is a pronounced dry period lasting several weeks between June and August, when the rainfall is less than 10 mm per month. Meteorological measurements were made on a 52-m high tower. The average tree height was 33 m, but some trees reached 44 m. The soil at the Reserva Jaru forest site is a medium-textured red-yellow podzol [*Hodnett et al.*, 1995]. The data between May 1992 and December 1993 were used in this study. Over this period, reasonably consistent hourly average data were collected using the automatic weather station, but there were some periods (up to five days) without data and some minor gaps, lasting less than a day. Latent (λE in W/m^2) and sensible heat (H in W/m^2) flux measurements were made in intensive observation periods between August and October in 1992 and between April and July in 1993.

3.1.2. ARM-CART Field Site (E13)

[16] The data set used was from station E13 of the Atmospheric Radiation Measurement Cloud and Radiation Testbeds (ARM-CART) program in the Southern Great Plains site (SGP) in Oklahoma. This site is located near Lamont, Oklahoma, at 36.605°N and 97.485°W at an elevation of 318 m. Meteorological measurements were taken on a 2.5-m tall tower. The data set covers the period April–July 1995 with a time interval of 30 min and includes all the necessary atmospheric forcings for the model and observational information on sensible heat (H in W/m^2) and latent heat fluxes (λE in W/m^2), soil temperature (T_g in K) as the average of five sensors that integrate the temperature over the top 5 cm, and the average of five soil moisture content measurements (S_w in weight of water per weight of dry soil) at a depth of 2.5 cm. The data are representative of the local- (small-) scale hydrometeorology and were collected over a flat cattle pasture plot with a Bowen ratio system.

3.1.3. Cabauw Field Site

[17] The Cabauw site is located on a polder (0.7 m below mean sea level) in the central portion of the Netherlands (51°58′N, 4°56′E). The surroundings of the instrument tower consist of meadows and ditches with scattered villages, orchards, and lines of trees [*Beljaars and Bosveld*, 1997]. The measurements are made in a grass field that is kept at a height of about 8 cm by frequent mowing. There are no obstacles within several hundred meters of the tower in all directions. In the predominant wind direction, the flow is unperturbed over an upstream distance of about 2 km. The vegetation cover is close to 100% year-round. The soil contains 35–55% clay. At Cabauw, the deep soil is saturated throughout the year, and evaporation is seldom limited by water supply [*Chen et al.*, 1997]. In this study, data used were made available by *Beljaars and Bosveld* [1997] for the entire year 1987. The observation height for the air temperature, wind speed, and specific humidity is 20 m. The annual total precipitation at this site for 1987 was 776 mm.

Table 2. BUCKET Model Parameters[a]

Index	Parameter Name	Physical Meaning of Parameters
1	soil1	initial value of soil moisture, mm
2	snow	initial value of water equivalent snow cover, mm
3	albsnf	albedo of fresh snow cover
4	albsnm	albedo of melting snow
5	albns	albedo of land surface
6	frfrza	fraction of moisture to allow into frozen soil
7	fcap	field capacity
8	frmelt	fraction of snowmelt into ground
9	drag	drag coefficient
10	Csoil	thermal inertia of soil, $J/m^2/k$
11	rncf	runoff coefficient
12	betad	critical value of Beta (as fraction)

[a]For Armcart, Tucson, and Reserva Jaru sites, "snow," "albsnf," and "albsnm" are fixed.

3.1.4. Illinois Field Site

[18] In August 1996, a flux measurement system was deployed within an agricultural area on the Reifsteck farm near Champaign, Illinois, in the GEWEX/GCIP north central region. Of special interest to the GEWEX/GCIP program is the cold season energy budget because it is affected by both land surface and hydrological processes. The site is typical of the agricultural cropland found throughout much of the midwestern United States. The farm has been in continuous "no till" since 1986, rotating yearly between a soybean and corn crop. The soil is a silt loam with 5% clay, 70% silt, and 25% loam. Data for this study were collected at a 30-min time step for the entire year of 1998 (1 January to 31 December) using an eddy covariance system. The soybean crop for 1998 had a planting date of 1 June and a harvest date of 10 October. Forcing data consisted of short-wave solar, net radiation, precipitation, temperature, wind speed, relative humidity, and pressure. Observations for this site include net radiation, sensible heat, latent heat and ground heat fluxes, skin temperature; soil temperatures at 5, 20 and 60 cm, and soil moisture measurements at 5, 20, and 60 cm. Carbon flux measurements were also collected at the Illinois site.

3.1.5. Tucson Field Site

[19] This field site is located at 32°13′N and 111°5′W in the semiarid, alluvial Sonoran Desert near Tucson, Arizona, USA, on a gently sloping terrain at an elevation of 730 m [*Unland et al.*, 1996]. Total precipitation measured over the yearlong sampling period was 275 mm. Vegetation heights range from a few centimeters for low grasses and bushes up to 7 m for the tallest saguaro cacti. Mean vegetation height is given as 1.2 m. Observations suggested a significant fraction of clay in the soil. Standard meteorological and micrometeorological measurements were taken over a 10-m tall tower from 12 May 1993 to 5 June 1994.

3.2. Models

[20] Five models were chosen for the present study to sample the span of model complexity. They are, in order of increasing complexity, the BUCKET model [*Manabe*, 1969], CHASM [*Desborough*, 1999], BATS1e [*Dickinson et al.*, 1993], Noah, [*Ek et al.*, 2003], and BATS2 [*Dickinson et al.*, 1998]. Detailed description of the models can be found in the references sited; only a short description of each of the models is given here.

3.2.1. BUCKET Model

[21] *Manabe* [1969] proposed a simple LSM based on earlier work by *Budyko* [1956]. The parameterization of the radiative and turbulent energy exchanges are in terms of a single-surface energy balance equation relating the energy fluxes to surface temperature. Evaporation is expressed as a simple function of the surface's plant-available moisture content and an energy-driven potential rate. Plant-available moisture is modeled explicitly, varying between wilting point and field capacity in response to precipitation input and evaporation output. Runoff is instantly produced when moisture is in excess of the field capacity. The code used here is similar to the one described by *Robock et al.* [1995] and *Schlosser et al.* [1997], with the important distinction that (the former did not incorporate) a consistent formulation of potential evaporation calculated using a hypothetically wet surface temperature is incorporated [*Schlosser et al.*, 1997]. A list of the parameter names and their physical meaning are presented in Table 2.

3.2.2. Chameleon Surface Model (CHASM)

[22] The CHASM modeling framework [*Desborough*, 1999] was originally presented and used to investigate the influence of surface energy balance complexity on LSM behavior. CHASM's hydrological parameterization is based on the BUCKET model, but has modifications that allow it to run with a variety of surface energy balance configurations. These range from the simple homogeneous surface of the BUCKET to a grouped mosaic structure with separate energy balances for each mosaic tile [e.g., *Koster and Suarez*, 1992] and with explicit treatment of transpiration, bare ground evaporation, and canopy interception as in the more complicated models that follow the *Deardoff* [1978] formulation (e.g., BATS). Parameterizations of intermediate complexity are constructed around a temporally invariant surface resistance. CHASM is designed so that all of its surface energy balance configurations use the same effective parameterization and parameters, thus allowing the impact of the configuration differences to be isolated. The definition of the model parameters is presented in Table 3. CHASM default mode, called SLAM that includes stability correction, surface resistance, canopy interception, bare ground evaporation, canopy resistance, and temperature differentiation [*Desborough*, 1999], is used in the present study.

Table 3. CHASM Model Parameters

Index	Parameter Name	Physical Meaning of Parameters
1	albg	albedo of bare ground
2	albn	albedo of snow
3	albv	albedo of vegetated surface
4	aleafm	leaf area index potential
5	aleafs	leaf area index seasonality parameter
6	fvegm	fractional vegetation potential
7	fvegs	fractional vegetation seasonality parameter
8	rcmin	minimum stomatal resistance, s/m
9	rhon	density of snow, kg/m^3
10	wrmax	moisture holding capacity for root zone, kg/m^3
11	zcol	soil color index [0–9]
12	z0g	roughness length of ground, m
13	z0n	roughness length of snow, m
14	z0v	roughness length of vegetated surface, m
15	ts	aerodynamic surface temperature, k
16	wn	available moisture in root zone, mm
17	wr	snow moisture equivalent, mm

Table 4. BATS 1e Model Parameters

Index	Parameter Name	Physical Meaning of Parameters
1	vegc	maximum fractional cover of vegetation
2	seasf	diff. between vegc and fractional cover at 269 K
3	rough	aerodynamic roughness length, m
4	displa	displacement height, m
5	rsmin	minimum stomatal resistance, s/m
6	xla	maximum area leaf index
7	xlai0	minimum area leaf index
8	sai	stem area index
9	sqrtdi	inverse sqrt of leaf dimension, $m^{-0.5}$
10	fc	light dependence of stamatal resistance, m^2
11	depuv	array for depth of surface soil layer, mm
12	deprv	array for depth of root zone soil layer, mm
13	deptv	depth of total soil layer, mm
14	albvgs	veg. albedo for wavelengths < 0.7 microns
15	albvgl	veg. albedo for wavelengths > 0.7 microns
16	rootf	ratio of roots in upper layer to in root layer
17	xmopor	fraction of soil that is voids
18	xmosuc	minimum soil suction, mm
19	xmohyd	maximum hydraulic conductivity of soil, mm/s
20	xmowil	fraction of water content at permant wilting
21	xmofc	ratio of field capacity to sat water content
22	bee	clapp and hornbereger "b" parameter
23	skrat	ratio of soil thermal conduct. to that of loam
24	solour	soil albedo for different colored soils
25	ssw	water in upper soil layer, mm
26	rsw	water in root zone layer, mm
27	tsw	water in total soil layer, mm

3.2.3. Biosphere Atmosphere Transfer Scheme Version 1e (BATS1e)

[23] BATS [*Dickinson et al.*, 1993] is a conceptual parameterization that consists of six interacting hydrometeorological components (three layers of soil, a canopy air component, a canopy leaf-stem component, and a snow covered portion). Together, these components simulate the various radiative and hydrological processes at the land-atmosphere interface.

[24] In principle, the BATS model computes the evolution of 12 state variables; namely, the temperature and water content for each of the six model components. However, two of these variables are not independent because the model assumes that the temperature of the lowest soil layer is constant and that, when snow cover is present, it has the same temperature as the upper soil layer. Thus BATS uses 10 water-energy conservation equations to solve for the dynamical evolution of the 10 independent state variables. The parameters of the model are given in Table 4. [Note: in BATS1e, the parameters *xmowil* and *xmofc* are not real parameters since they are computed from some of the other parameters, but are here described as such because they were in the original model description.]

3.2.4. Noah Model

[25] The Noah model [*Ek et al.*, 2003; *Mitchell et al.*, 2000] is one of the evolving community (i.e., multigroup) land surface models that traces its origins to the OSU-LSM [*Mahrt and Pan*, 1984]. The Noah model was chosen for evaluation for several reasons. It has been used in previous studies by this research group and demonstrated a good performance for another semiarid site [*Hogue et al.*, 2006]. More importantly, the model is currently parameterized for use over semiarid regions in the National Centers for Environmental Prediction (NCEP) North American Land Data Assimilation System (NLDAS) [*Mitchell et al.*, 2004] of the National Weather Service (NWS). Updates of the model are posted periodically on the NCEP Web site (online at ftp://ftp/ncep.noaa.gov/pub/gcp/ldas/Noahlsm); version 2.5.1 is used in this analysis (release date: 5 March 2002).

[26] The Noah model contains four soil layers: a thin 10-cm top layer, a second root zone layer of 20 cm, a deep root zone of 60 cm, and a subroot zone of 110 cm. It can be run for 13 vegetation covers (2 of which use the same parameter values) and nine different soil types (two of which also use the same parameters). A local greenness fraction is computed from the Normalized Difference Vegetation Index (NDVI) to establish seasonality in the model for each of the 13 vegetation types. The leaf area index (LAI) value is typically held constant (or used as a tuning parameter) instead of also being varied seasonally [*Gutman and Ignatov*, 1998]. Consequently, the LAI parameter was included as a parameter to be calibrated, while the monthly greenness fraction was obtained from NCEP and not adjusted. Table 5 contains a description of the model parameters.

3.2.5. Biosphere Atmosphere Transfer Scheme Version 2 (BATS2)

[27] The modifications made to BATS between the original and revised versions include a revised stomatal conductance model and the inclusion of a growth model [*Dickinson et al.*, 1998]. The original version of BATS represents 15 biomes by prescribing a seasonally varying fractional vegetation cover, albedo, and leaf area index (LAI), the LAI being calculated as a function of temperature between prescribed maximum and minimum values. In BATS2, this prescribed LAI behavior is replaced with a

Table 5. BATS 2 Model Parameters

Index	Parameter Name	Physical Meaning of Parameters
1	vegc	maximum fractional cover of vegetation
2	sla	single-side leaf area
3	tdlef	Leaf freezing temperature, k
4	wdpool	flag for existence of wood
5	wrrat	wood to nonwood ratio
6	seasf	diff. between vegc and fractional cover at 269 K
7	rough	aerodynamic roughness length, m
8	displa	displacement height, m
9	rsmin	minimum stomatal resistance, s/m
10	xla	maximum area leaf index
11	xlai0	minimum area leaf index
12	sai	stem area index
13	sqrtdi	inverse sqrt of leaf dimension, $m^{-0.5}$
14	fc	light dependence of stomatal resistance, m^2
15	depuv	array for depth of surface soil layer, mm
16	deprv	array for depth of root zone soil layer, mm
17	deptv	depth of total soil layer, mm
18	albvgs	veg. albedo for wavelengths < 0.7 microns
19	albvgl	veg. albedo for wavelengths > 0.7 microns
20	rootf	ratio of roots in upper layer to in root layer
21	xmopor	fraction of soil that is voids
22	xmosuc	minimum soil suction, mm
23	xmohyd	maximum hydraulic conductivity of soil, mm/s
24	xmowil	fraction of water content at permant wilting
25	xmofc	ratio of field capacity to sat water content
26	bee	clapp and hornbereger "b" parameter
27	skrat	ratio of soil thermal conduct. to that of loam
28	solour	soil albedo for different colored soils
29	ssw	water in upper soil layer, mm
30	rsw	water in root zone layer, mm
31	tsw	water in total soil layer, mm
32	lfmass	leaf mass, g/m^2
33	fastcp	short-lived carbon, g/m^2
34	rtmass	mass of fine roots, g/m^2
35	wood	mass of wood, g/m^2
36	stblcp	stable carbon pool, g/m^2

Table 6. Noah 2.51 Model Parameters

Index	Parameter Name	Physical Meaning of Parameters
1	rcmin	minimum stomatal resistance, s/m
2	rgl	used in solar radiation term of canopy res
3	hs	used in vap. pres. deficit term of canopy res
4	z0	roughness length, m
5	lai	leaf area index
6	cfactr	canopy water parameter
7	cmcmax	second canopy water parameter, m
8	sbeta	used in calc. of veg. effect on soil heat flux
9	rsmax	maximum stomatal resistance, s/m
10	topt	optimum transpiration air temperature, K
11	maxsmc	porosity
12	drysmc	air dry soil moisture content limits
13	psisat	saturated soil potential
14	satdk	saturated soil hydraulic conductivity, m/s
15	b	the "b" parameter
16	satdw	saturated soil diffusivity
17	quartz	soil quartz content
18	nroot	number of root layers
19	refdk	reference value for sat. hydraulic conductivity
20	fxexp	bare soil evaporation exponent
21	refkdt	reference value for surface infiltration parameter
22	czil	to calculate roughness length of heat
23	csoil	soil heat capacity for mineral soil component
24	zbot	depth of lower boundary soil temp, m
25	frzk	ice threshold (above frozen soil is impermeable)
26	xnup	threshold snow depth (100% snow cover), m
27	snoalb	maximum albedo over deep snow
28	salp	shape of dist. function of snow cover
29	slope	average terrain slope

modeled seasonal evolution. The concepts used to describe carbon assimilation follow those of *Farquhar et al.* [1980]. The equation linking carbon assimilation and stomatal conductance, the reciprocal of stomatal resistance, is a derivative of that given by *Ball et al.* [1987]. The whole canopy stomatal resistance is then obtained by dividing the average stomatal resistance by the LAI. The assimilated carbon is allocated into the components of the vegetation, i.e., leaves, wood, and roots, in a growth model. The carbon stored in these components plus that stored in the soil, the Net Primary Productivity (NPP), and the carbon flux to the atmosphere is computed at each time step. The growth model then returns the updated LAI to BATS2. The parameters of the model are presented in Table 6.

4. Sensitivity Analysis Using Multicriteria Methods

[28] The multicriteria approach provides a more rigorous framework for analysis of multi-input/multi-output models of dynamic earth system responses than the traditional single-criterion approach [*Gupta et al.*, 1998]. The multi-objective generalized sensitivity analysis (MOGSA) algorithm [*Bastidas*, 1998] was developed as a multicriteria extension of the generalized sensitivity analysis (GSA)–that later became known as the regionalized sensitivity analysis (RSA) approach [*Spear and Hornberger*, 1980; *Hornberger and Spear*, 1981; *Spear et al.*, 1994] for testing the identifiability of environmental models. The RSA methodology establishes the sensitivities of individual parameters by examining whether a priori distributions of the parameters are statistically different under a specific behavioral classification, via the Kolmogorov-Smirnov (KS) two-sample test: the smaller the KS probability, the more sensitive the parameter. By introducing the Pareto ranking concept [*Goldberg*, 1989] as the technique for selecting the discriminatory threshold for behavioral and nonbehavioral parameter sets, MOGSA takes into account the multicriteria nature of typical sensitivity problems of environmental models. To overcome the effect that specific sampling procedures may have on the outcome of the sensitivity analysis MOGSA uses bootstrapping [*Efron*, 1979a, 1979b] to determine the median (a robust statistic [*Rousseeuw*, 1991]) of the KS probability value.

[29] In the implementation of MOGSA, a number of samples (i.e., parameter sets) are randomly chosen from the predefined feasible parameter space and the error function (EF) values are calculated for each sample. On the basis of the corresponding EF values, the samples are then ranked using Pareto ranking and an arbitrary rank threshold is used to partition the samples into behavioral and nonbehavioral groups. The K-S test is performed on the two sets to estimate the multicriteria (or global) sensitivity of each parameter. The test is repeated using the bootstrapping procedure (i.e., resampling with replacement) to reduce the sampling dependence of the results. This process is repeated with successively larger sample sizes until the total number of sensitive parameters stabilizes. Different Pareto rank thresholds may also be used to test the sensitivity to the choice of the threshold. A certain threshold, for which the sample size required for stability is smallest and the number of sensitive parameters is largest, is then chosen to decide the final global sensitivities. Once the global sensitivities (i.e., multicriteria sensitivities) have been estimated, the corresponding quantile of the error function value is used as the discerning threshold to decide the sensitivity of a single objective. Further details are provided by *Bastidas* [1998] and *Bastidas et al.* [1999].

[30] The main advantage of the MOGSA algorithm is that it automatically includes the possible parameter interactions and provides a "global sensitivity" value along with sensitivities to specific responses of the model, for example, sensible heat, latent heat, soil moisture, etc. At the same time, on the basis of the values for the median of the KS statistic, an objective ranking of the sensitivity level can be obtained. Also, in the present work, we show that MOGSA is not complex in its implementation and thus is a good candidate for conducting thorough sensitivity analysis among large numbers of LSMs. Although the original MOGSA algorithm suffered from the sensitivity results being dependent on the selected parameter range, that disadvantage has been overcome by using the approach presented by *Demarty et al.* [2004], which screens out ranges that produce severe nonbehavioral error function values.

5. Results

[31] To achieve the goals stated in section 1 the MOGSA algorithm was run for each model at all sites using prespecified parameter ranges (ranges available from the authors). Table 7 presents the number of sensitive parameters for each model at each study site; the upper part of the table presents the raw number of sensitive parameters and the lower part of the table represents the ratio of sensitive to total number of parameters (total number in parentheses). The average

Table 7. Number of Sensitive Parameters for Each Model at Different Sites

	Raw Number of Sensitive Parameters				
Sites	BUCKET (9/12[a])	CHASM (17)	BATS 1e (24)	BATS 2 (28)	Noah (29)
ARMCART	2	7	9	12	18
Cabauw	6	6	13	14	13
Illinois	1	11	12	14	20
Reserva Jaru	5	3	10	12	16
Tucson	2	7	12	12	14
average	3.2	6.8	11.2	12.8	16.2
	Percentage Ratio of Sensitive Parameters to Total				
Sites	BUCKET (12)	CHASM (17)	BATS 1e (24)	BATS 2 (28)	Noah (29)
ARMCART	22.22	41.18	37.50	42.86	62.07
Cabauw	66.67	35.29	54.17	50.00	44.83
Illinois	11.11	64.71	50.00	50.00	68.97
Reserva Jaru	55.56	17.65	41.67	42.86	55.17
Tucson	22.22	41.18	50.00	42.86	48.28
average	35.56	40.00	46.67	45.71	55.86

[a]Three snow parameters were fixed at ARMCAT, R Jaru, and Tucson.

number of sensitive parameters and corresponding ratio are also listed for each model for each of the five sites. For the BATS 1e, Noah, and BATS 2 models, fewer parameters are actually analyzed for sensitivity than those listed in Tables 4–6. This is because we are not including the initial soil water content for the different layers and in the case of the BATS2 parameters are calculated during model simulations or are set at prefixed values (eight parameters); also five carbon parameters were not analyzed as part of this sensitivity analysis because of a lack of carbon flux data at the given sites.

[32] The number of sensitive parameters in the models varies from an average of around three for the simple BUCKET model to an average of 16 sensitive parameters for the more complex Noah model. The BATS1e model has an average of around 11 sensitive parameters, while the BATS2 has on average 13 parameters that are sensitive at the various sites. An alternative comparison index is the ratio of sensitive parameters to the total number of parameters analyzed; this index will be referred to as the "relative" number of sensitive parameters. In general, the relative index increases with an increasing number of model parameters, from 0.356 for the BUCKET model to 0.559 for the Noah model. However, when going from the BATS1e (relative index 0.467) to the more complex, but with a similar structure, BATS2 model (relative index 0.457) there is actually a decrease in the relative number of sensitive parameters for three of the sites (ARM-CART, Cabauw, and Tucson). Although the BATS2 model has become more commonplace in modeling studies because of its growth model and carbon assimilation processes, our study indicates that the model has lost some sensitivity, possibly because of overparameterization or compensation of interacting parameters.

[33] There is no clear trend in the number of sensitive parameters at a specific site as complexity increases. For example, the Cabauw and Reserva Jaru sites (the more humid study sites) have the most sensitive parameters with the BUCKET model; however, as complexity increases, the number of sensitive parameters does not necessarily increase. In fact, with the more complex Noah model, the Cabauw site actually has a smaller relative index, 0.448. In contrast, at Illinois the BUCKET has only one sensitive parameter (of 11) while the other models show stronger sensitivity. This latter result may be related to the parameterization of cold weather processes or insensitivity to saturated conditions in the more complex models. The Cabauw site is the most northern site in the study and is a site where the soils are saturated year-round [*Beljaars and Bosveld*, 1997]. Most high-latitude regions experience snow accumulation. The albedo of this snow surface significantly moderates the energy exchange between the land surface and the atmosphere, reflecting more of the short-wave radiation back to the atmosphere.

[34] A sensitivity analysis based on groupings of (1) vegetation parameters and (2) soil and snow parameters is also of interest. Snow and soil parameters were grouped together for this analysis. Initial condition parameters were not included as part of either group. The BUCKET model does not explicitly contain any parameters related to vegetation dynamics. In general, the BATS1e, BATS2, and Noah models show an even distribution between vegetation and soil parameter sensitivity, with similar index values for soil and vegetation parameters. Interestingly, the CHASM model shows much more sensitivity to vegetation parameters (highest relative index) than to soil parameters, possibly because the CHASM model structure used in this analysis consists of a fairly simple bucket structure with a more complex vegetation representation. Of the three more complex models, the BATS1e again has a higher index for soil than either the BATS2 or Noah models. BATS1e and BATS2 are similar in the relative index of vegetation parameters (0.440 and 0.466), and the Noah model has the lowest index for vegetation parameters. This is somewhat disconcerting for the BATS2, which includes a much more advanced vegetation parameterization than either the BATS1e or Noah models; hence one would expect higher sensitivity to vegetation than the other models. A sensitivity analysis which would include carbon parameters may alter these results and should be an issue for further study at sites where more carbon flux data are readily available.

[35] Some general comments can be summarized from this sensitivity analysis.

[36] 1. A simpler land surface model does not necessarily result in more identifiable or sensitive parameters for a site; in fact, the opposite appears to be the case in this analysis. The more complex models have a larger relative index of sensitive parameters, although this varies somewhat with the vegetation sites. The BATS1e is most sensitive to the more semiarid sites, ARM-CART and Tucson. BATS2 has the most sensitivity to the Illinois site, while the Noah model has the most sensitivity to the crop sites, ARM-CART and Illinois. As land surface models become more complex, these results are somewhat encouraging because the additional parameters do not necessarily result in model overparameterization.

[37] 2. The preceding statement appears to hold true only to a certain level of complexity. The Noah model has the highest relative sensitivity index of parameters in this analysis. However, when moving from the BATS1e to the more complex BATS2 model, there is actually a decrease in the average number of sensitive parameters. The more complex BATS2 has less overall sensitivity than its prede-

cessor, BATS1e. Only the Cabauw and Reserva Jaru sites have slightly more sensitive parameters in the BATS2 model. The fact that most of the developments of the Noah model were made using the Illinois site may be reflected in the high sensitivity level at that site.

[38] 3. The sensitivity of the parameters in this study is also probably linked to the atmospheric forcings (input data) used in the analysis. The different environments used in the analysis (wetter sites (i.e., Reserva Jaru) vs. drier sites (i.e., Tucson)) lead to various levels of activation in model processes, resulting in different sensitive parameters for the study sites.

5.1. Global Sensitivity Model Specific Comments

[39] When analyzing the sensitivity plots for each site and model, more specific comments can be made regarding the parameter sensitivities. Figure 1 presents the results grouped by model for all the different sites. In all the plots, the values further away from the center represent an increased sensitivity index for the corresponding parameter. The red and green dashed circles correspond to our predefined (heuristically) levels of medium (5% significance level) and high sensitivity (1% significance level). Parameters inside the red circle (significance level > 5%) are considered insensitive.

5.1.1. BUCKET Model

[40] In comparison to the other models used in this analysis, the BUCKET model has the lowest relative index (0.317). The drag coefficient (*drag*), influencing momentum, is the only parameter sensitive at all sites. *Csoil* is sensitive at four of the five sites, all but the Illinois site. Both ARM-CART and Tucson, the two more arid sites in this study, had the same two sensitive parameters (*drag* and *Csoil* (thermal inertia of soil)). Interestingly, the Cabauw site is sensitive to the three albedo values (fresh snow, old or melting snow, and land surface) along with the initial snow water equivalent value. Reserva Jaru is the only site where the field capacity parameter (*fcap*) and the initial soil moisture conditions (soil) are sensitive. Three of the BUCKET parameters show insensitivity at all sites: *fmelt* (fraction of snowmelt infiltrating), *mcf* (runoff coefficient), and *betad* (critical value of Beta (as fraction)). Because streamflow was not used as a criterion or variable in this analysis, few conclusions can be drawn on the insensitivity of the runoff coefficient. It is expected this result may change if streamflow or runoff data were used as a criterion in a sensitivity analysis.

5.1.2. CHASM Model

[41] In the CHASM model analysis 14 parameters and three initial states were all involved in the model simulations. All three initial states in the model (surface temperature, soil moisture, and snow water equivalent) were analyzed as parameters. The snow water equivalent (*wn*) value was insensitive at all sites, even the snow regions (Illinois and Cabauw), and the initial soil moisture (*wr*) was only sensitive at the ARM-CART site. Interestingly, the initial surface temperature (*ts*), however, was sensitive at all sites.

[42] Of the vegetation and soil parameters, the CHASM model shows more sensitivity to the vegetation parameters than the soil parameters, most likely because of the simpler soil representation. Two of the CHASM vegetation parameters (fractional vegetation potential (*fvegm*) and the minimum stomatal resistance (*rcmin*)) were sensitive at all sites. The fractional vegetation seasonality parameter (*fvegs*) is sensitive at four of the five sites (insensitive at Rjaru). The insensitivity of the seasonality parameter is consistent with the evergreen broadleaf vegetation of the tropical rain forest. Of the remaining 14 parameters, two vegetation parameters (*aleafm* and *aleafs*−both leaf area index parameters) along with the snow density parameter (*rhon*) and the soil color index (*zcol*) were insensitive at all sites. The Illinois site contains the most sensitive parameters using CHASM; 11 of the 17 parameters show high sensitivity to the criterion. The more complex vegetated site, Reserva Jaru, contains only three sensitive parameters: *fvegm, rcmin*, and the initial temperature (*ts*).

5.1.3. BATS1e Model

[43] Of the models used in this study, the BATS1e has the highest overall number of sensitive parameters. During this analysis, only two of the 27 parameters were held fixed in the model, *xmowil* and *xmofc*, because these are calculated during model simulations. Of the three initial states in the model, the upper soil layer moisture (*ssw*) was sensitive at all sites. Tucson was the only site where the initial soil moisture values in each layer (*ssw, rsw*, and *tsw*) were sensitive in the model. The BATS1e model shows fairly even distribution between the number of sensitive vegetation parameters and sensitive soil parameters. The ARM-CART site has the most sensitivity to vegetation, with six of ten parameters showing sensitivity. Cabauw, Illinois, and Tucson only have four sensitive vegetation parameters out of the ten vegetation parameters in the model. Surprisingly, there are only three vegetation parameters sensitive at the Reserva Jaru site. The Tucson site has the largest number of sensitive soil parameters, eight of 12. This seems to be consistent, as the vegetation cover at this site would not seem to play as big a role in the large sensible heat fluxes in the region. The Tucson site was also the most sensitive to initial conditions, with sensitivity to the initial moisture in all three zones (surface, root, and total). Cabauw has the least number of sensitive soil parameters, five of the 12 values. Several parameters were sensitive at all sites: two vegetation parameters, fractional vegetation cover (*vegc*) and maximum leaf area index (*xla*), and three soil parameters: depth of the upper soil layer (*depuv*), the root fraction (*rootf*), and porosity (*xmopor*). Several other important parameters were also sensitive at only some of the sites. Minimum stomatal resistance (*rsmin*) was sensitive at three of the sites (ARM-CART, RJaru, and Tucson). The Clapp and Hornberger “b” parameter was sensitive at four of the sites, not at the RJaru site. The BATS1e model only shows three of the 25 parameters, which are insensitive at all sites: the seasonality fraction (*seasf*) and two soil parameters, depth of the total soil layer (*deptv*) and the short-wave albedo parameter (*albvgs*).

5.1.4. BATS2 Model

[44] The BATS2 model had on average ten sensitive parameters for the five sites. The Illinois site has the most sensitive parameters (12), and RJaru has the least sensitive parameters with eight. Of the vegetation and soil parameters, the BATS2 model actually has the fewest parameters sensitive to the vegetation at the RJaru site, which has the most mature and complex vegetation of the sites in the study. This is an interesting outcome, as the BATS2 model was specifically developed to have an improved vegetation

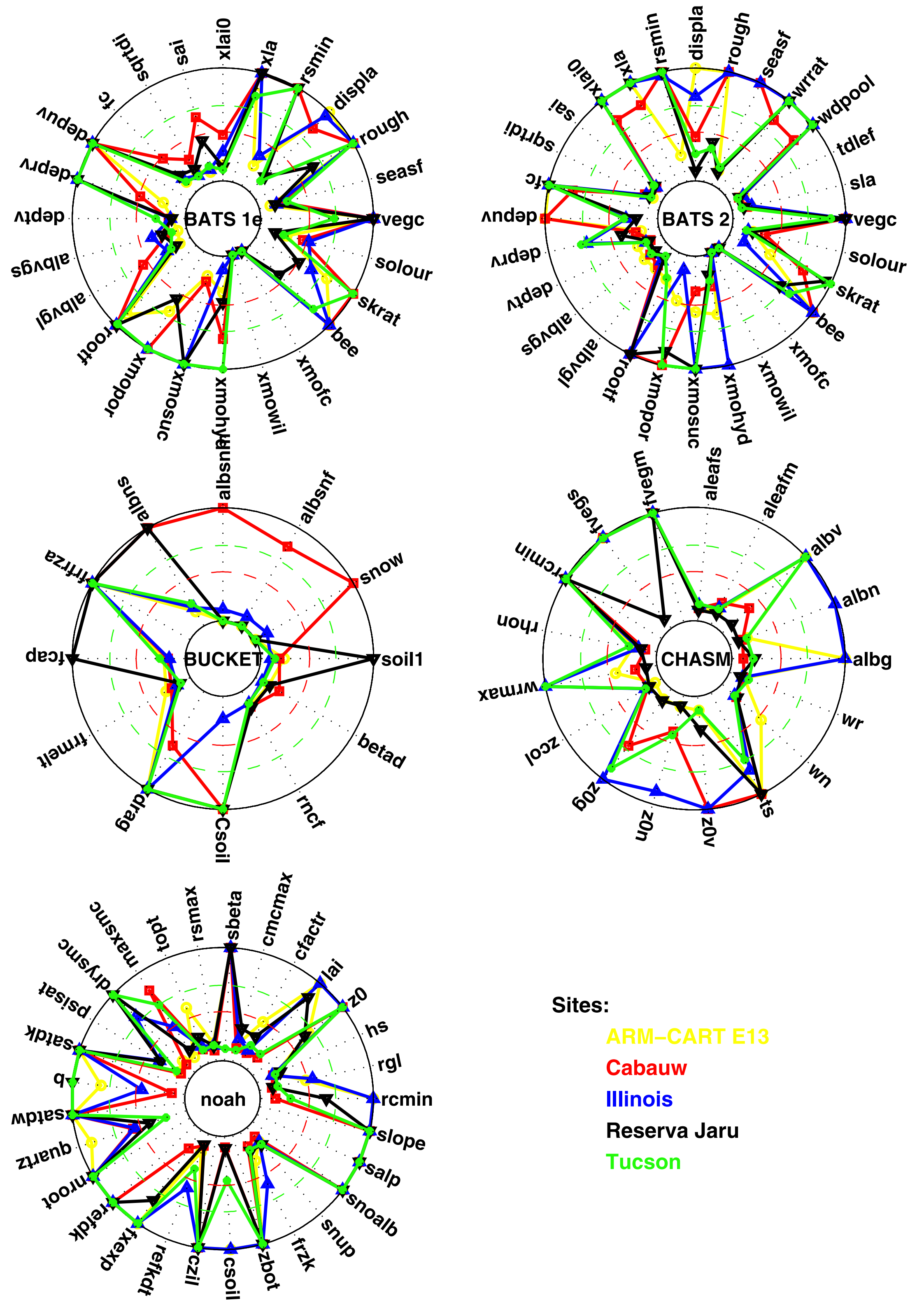


Figure 1. Sensitivity analysis plots for the BUCKET, CHASM, BATS 1e, BATS 2, and Noah models at the different sites. The values represented are those of the multicriteria "global" sensitivity index, i.e., sensitivity to sensible head, latent heat, and ground temperature combined. The farther away from center, the more sensitive the parameter. The dotted lines correspond to the 0.05 and 0.01 significance levels and are associated with thresholds for moderate and high sensitivity. The plots are grouped by model.

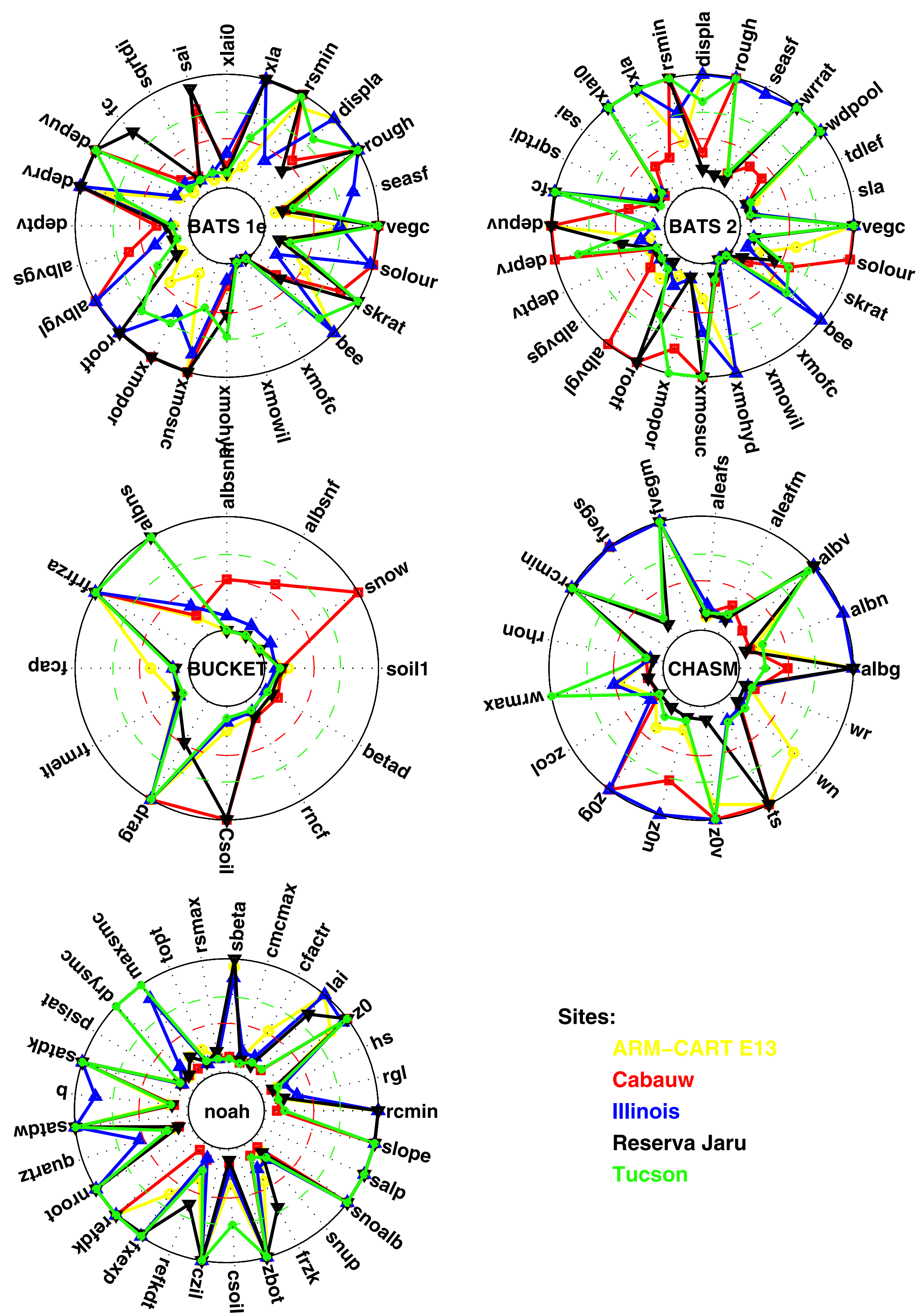


Figure 2. Same as Figure 1 but for the sensible heat sensitivity.

parameterization, able to simulate the growth and decay of vegetation. Four of the sites have fewer sensitive parameters in BATS2 (than BATS1e) parameters, with only the Cabauw site having more sensitivity with the BATS2, and this is only one more parameter. At all of the sites, five of the soil parameters were sensitive (index of 0.417), although these were not the same parameters throughout. Three of the BATS2 parameters are sensitive at all the sites: vegetation cover (*vegc*), minimum stomatal resistance (*rsmin*), and the Clapp and Hornberger "b" (*bee*) parameter. These findings are also consistent with *Bastidas et al.* [1999] in the BATS1e model (and as in the previous section). *Lettenmaier et al.* [1996] also found the "b" parameter to be sensitive in the PILPS 2-c studies. Several of the BATS2 parameters are insensitive in all models, including single-side leaf area (*sla*), stem area index (*sai*), inverse square root of leaf dimension (*sqrtdi*). This is also consistent with the BATS1e findings at the Tucson site [*Bastidas et al.*, 1999].

5.1.5. Noah Model

[45] The Noah model (version 2.5.1) contains the most parameters of any of the models in this study; however, 12 of the 49 parameters are initial conditions that need to be estimated. Eight of the parameters relating to initial soil moisture were included in the sensitivity analysis, while the initial temperatures of the soil zones were not. Of the remaining 37 parameters, 24 were included for analysis and 13 were set to default values. The number of soils layers (*nroot*) in this analysis was set to four. The model had on average 15 of 32 sensitive parameters (0.475), varying from nine for the Cabauw site, to 20 for the ARM-CART site. Following the BATS1e model, the Noah model has the most sensitive parameters. Of the vegetation parameters, ARM-CART had the highest sensitivity, at an index of 0.700. The roughness length parameter (*z0*), along with four soil parameters, saturated hydraulic conductivity (*satdk*), saturated soil diffusivity (*satdw*), reference value for saturated hydraulic conductivity (*refdk*), and a parameter used in the calculation of roughness length of heat (*czil*), were sensitive at all the sites. Five of the Noah parameters were insensitive at all sites, three vegetation parameters: canopy resistance function parameter (hs), second canopy water parameter (*cmcmax*), and the maximum stomatal resistance (*rsmax*); one soil parameter: saturated soil potential (*psisat*).

5.1.6. General Sensitivity Summary

[46] As discussed above, several of the parameters were clearly either insensitive or sensitive at *all* of the analyzed sites for each of the models. The BUCKET model has three parameters (of the 12 in the model) that are insensitive at each of the sites. Of the more complex models, the BATS2 and Noah models have five and six parameters, respectively, that were insensitive to all of the study sites. With the increasing number of parameters in the models, a broad sensitivity analysis, such as that performed here, can be undertaken to determine which parameters within the models are relevant. It is apparent that some parameters are important to the modeling process, while others are not, no matter to which biome they are applied. These insensitive parameters can probably be safely set to default values to reduce the dimensionality of the parameter estimation problem for the various land surface models, regardless of the application site. Development of a systematic approach for defining sensitive and insensitive parameters, such as that used in this analysis, allows insight into the degree of difficulty of the parameter estimation problem and which parameters explicitly influence the modeling process.

5.2. Single Criterion Sensitivity Behavior

[47] As in the case of global sensitivity, Figures 2–4 present the results for the single criterion sensitivity analysis grouped by model. Figure 2 represents the parameter sensitivity to sensible heat flux, Figure 3 to latent heat flux, and Figure 4 to the ground temperature. As in the global sensitivity case, in all the plots, the values further away from the center represent an increased sensitivity index for the corresponding parameter. The red and green dashed circles correspond to the heuristically predefined levels of medium (5% significance) and high sensitivity (1% significance). Parameters inside the red circle (significance >5%) are considered insensitive.

[48] Overall, it is of interest to note how the shapes of the polygons change, representing the changes in the sensitivity levels and the effects of the parameter interaction. It is also of interest that the sensitivity for the sensible heat and the ground temperature are more similar than the sensitivities between sensible and latent heat. This is physically meaningful, and speaks to the discerning power of the MOGSA methodology, because the sensible heat is calculated as a gradient of temperatures; for example, the sensible heat and the ground temperature sensitivities at the Cabauw site for the BUCKET model or the Noah model at the Tucson site. It is also of interest to note that when the parameters are highly sensitive to at least one of the fluxes (sensible or latent heat) or a state variable (ground temperature) an overall sensitivity is automatically achieved in almost all the cases; an exception will be the *solour* parameter for the BATS 1e and BATS 2 models for all the sites.

5.3. Sensitivity Analysis Across Models

[49] In the following section we present a detailed global (multicriteria) sensitivity analysis of parameters with similar physical meaning in models with different complexity (recall that we use the number of parameters as a proxy for complexity).

5.3.1. Models With Different Structure

[50] First we examine across four models the parameters selected to represent both soil and vegetation submodels. The parameters were chosen so that they represent actual measurable physical parameters such as the fractional vegetation cover and also "process parameters" such as the soil porosity or hydraulic conductivity. The actual names of the parameters change from model to model but we have selected seven parameters and ascribed to them names. Table 8 describes those names and the corresponding physical meaning.

[51] The CHASM, BATS1e, BATS2, and Noah model parameters were included in this analysis; the BUCKET model does not explicitly contain any of the parameters chosen for this study and is therefore excluded. The goal of this detailed analysis is to investigate the parameterization or "physical meaning" of these parameters within different model structures for land surface models, whether the meaning is consistent from model to model, and if the sensitivity varies between same site/different models and same model/different sites.

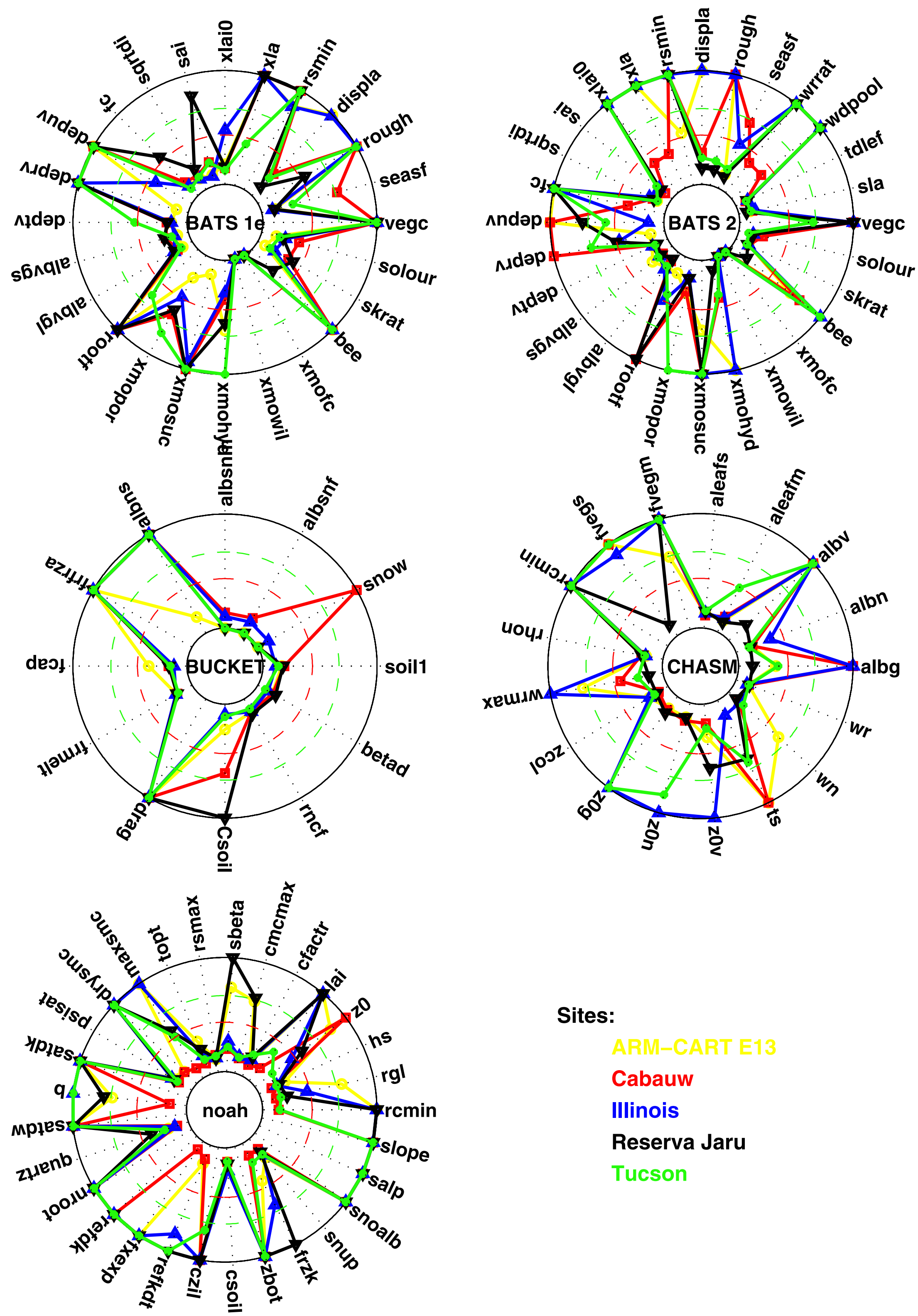


Figure 3. Same as Figure 1 but for the latent heat sensitivity.

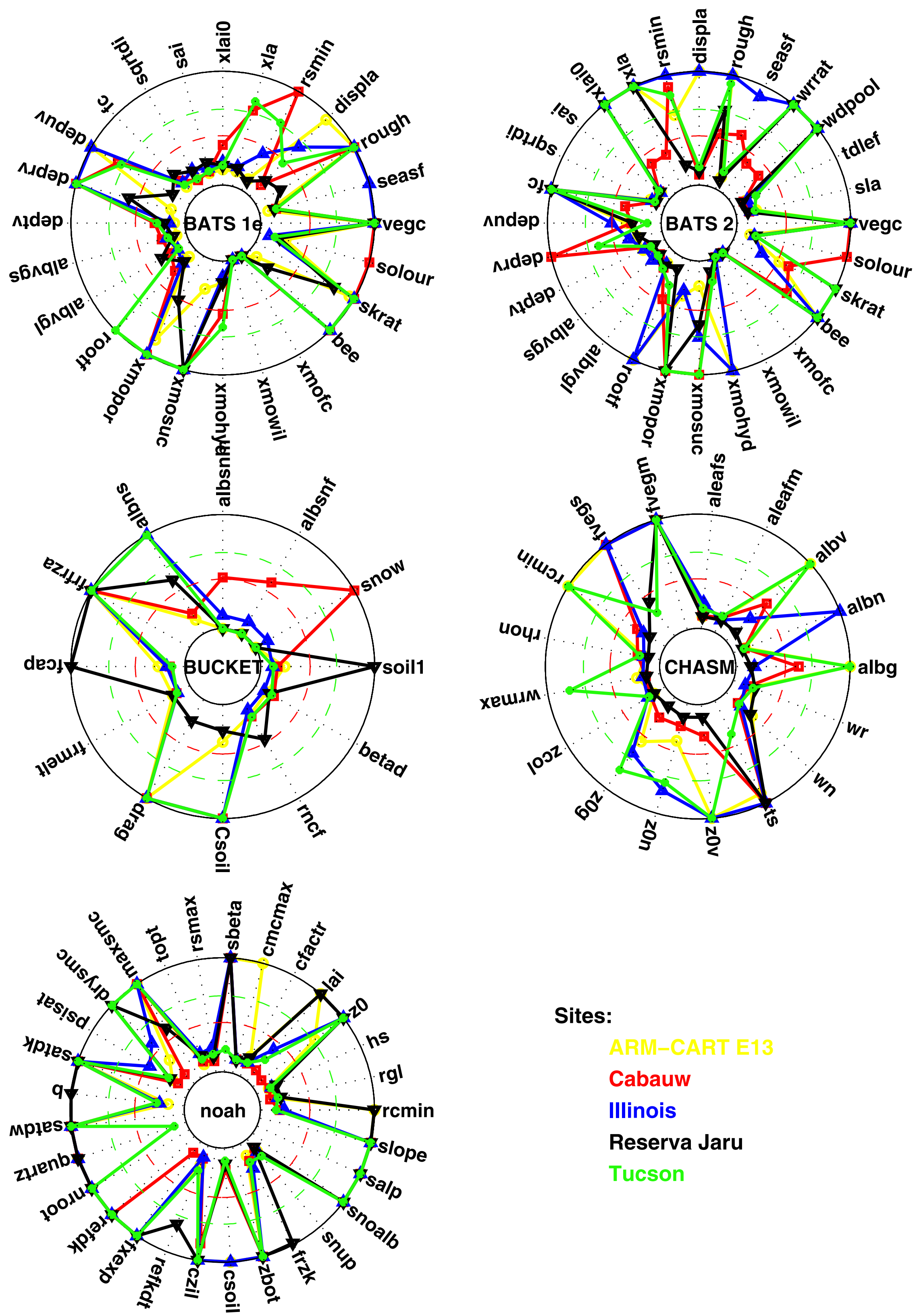


Figure 4. Same as Figure 1 but for the ground temperature sensitivity.

Table 8. Similar "Physical Meaning" Parameters Chosen for Across Model Sensitivity Analysis

	Parameter Name				
Analysis	CHASM	BATS 1e	BATS 2	Noah	Parameter Physical Meaning
fveg	fvegm	vegc	vegc	n/a	fractional vegetation cover
rough	z0v	rough	rough	z0	roughness length
displa	n/a	displa	displa	n/a	displacement height
rsmin	rcmin	rsmin	rsmin	rcmin	minimum stomatal resistance
poros	n/a	xmopor	xmopor	maxsmc	soil porosity
hydcond	n/a	xmohyd	xmohyd	satdk	soil hydraulic conductivity
b	n/a	bee	bee	b	Clapp and Hornberger "b" parameter

[52] The parameters selected are listed in Table 8. They include four vegetation parameters: fractional vegetation cover, aerodynamic roughness length, displacement height, and minimum stomatal resistance, and three soil parameters: porosity, maximum saturated hydraulic conductivity, and the Clapp and Hornberger "b" parameter. Several of these parameters have been listed in the literature as being important or sensitive in representing land surface processes [e.g., *Bastidas et al.*, 1999; *Driese and Reiners*, 1997; *Lettenmaier et al.*, 1996; *Gao et al.*, 1996; *Henderson-Sellers and Brown*, 1992; *Liang and Guo*, 2003]. The seven parameters are common to many of the recently developed models. The fractional vegetation cover (*fveg*) in the models is a parameter that varies between a minimum and maximum value during the growing season, typically based on the subsurface soil temperature. Any snow cover on vegetation reduces this fractional vegetation, as this part of the land surface does not interact with the atmosphere. The roughness length (*rough*) is used to express the roughness of the surface and is typically a fraction of the land surface cover or vegetation height. It affects the intensity of mechanical turbulence and the various fluxes above the surface. A lower roughness length implies less exchange between the surface and the atmosphere. The minimum resistance (or maximum conductance) encountered by diffusion of water moving from inside the leaf (or canopy) to the outside is referred to as the minimum stomatal resistance (*rsmin*). This can occur through leaf stomata or cuticles and changes with environmental conditions [*Dickinson et al.*, 1993]. The parameter is used in the calculation of overall stomatal resistance of the canopy. Displacement height or zero plane displacement height (*displa*) is used in the determination of aerodynamic resistance of the surface. Porosity and hydraulic conductivity have the same definitions found in classical hydrogeology, with porosity (*poros*) defined as the volume of voids in the soil fraction and hydraulic conductivity (*hydcond*) defined as the constant in Darcy's law, which relates hydraulic gradient to specific discharge. Porosity is used in estimating maximum saturated conditions in each of the soil zones in the layers, while hydraulic conductivity is used to define gravitational drainage or flow from the soil layers. Clapp and Hornberger's "*b*" parameter is a nondimensional soil texture parameter relating changes in soil water potential and hydraulic conductivity with soil water.

[53] The CHASM model contains three of the chosen parameters, the BATS1e and BATS2 contain all seven, and the Noah model contains five of the parameters. Figure 5 displays the global sensitivity indices for each of the parameters with each model grouped by study site. It can be seen that the vegetation cover parameter (*fveg*) is sensitive at all sites in the three models, which explicitly contain this parameter. However, there is variability in several of the other parameters in the models. The displacement height (*displa*) parameter in BATS1e and BATS2 has variable sensitivity from site to site. This is also true of the minimum stomatal resistance (*rsmin*) parameter in the Noah model and the porosity parameter in BATS2 and Noah. Hydraulic conductivity in BATS1e and BATS2 changes significantly from site to site, as does the "*b*" parameter in the Noah model.

[54] The vegetation cover (*fveg*) is sensitive for all of the models (CHASM, B1, and B2) at the ARM-CART site. However, the roughness parameter (*rough*) is insensitive in the CHASM model, but is sensitive in Noah and highly sensitivity for Bats 1 and Bats 2. Other notable results at ARM-CART: the minimum stomatal resistance (*rsmin*) is insensitive in both BATS models yet is highly sensitive in CHASM and Noah. Two of the soil parameters, porosity and hydraulic conductivity (K) also vary significantly at ARM-CART. Porosity in the Noah model is insensitive, while BATS1e hydraulic conductivity is insensitive. At the Cabauw site, there is an obvious difference in how the displacement height behaves in the BATS1e and BATS2 models (sensitive at B1 and insensitive at B2). Another large difference is shown for *rsmin*, sensitive in three of the models and very insensitive for the Noah model, which is also the case for the Clapp and Hornberger "*b*". At the Illinois site, large discrepancies are seen in how the BATS1e and BATS2 sensitivities compare for *poros* and *hydcond*. The Reserva Jaru site is also inconsistent in sensitivities for the soil parameters; porosity is sensitive for BATS1e and BATS2, but insensitive for the Noah model. The opposite is true for the hydraulic conductivity parameter. The Tucson site shows the most intermodel variability in sensitivity, most likely attributable to the difficulty of most LSS to represent semiarid processes. The *fveg* is again sensitive in all models; however, the roughness length shows high variability between models. CHASM and BATS2 are insensitive to this parameter, but BATS1e and the Noah model are sensitive. Interestingly, these are also the two models that performed the best at the semiarid site. Displacement height does not appear to be important at the Tucson site, but minimum stomatal resistance is sensitive in three of the models (not the Noah model). For the soil parameters, porosity is sensitive in all models, while hydraulic conductivity is only sensitive in BATS1e. The Clapp and Hornberger "*b*" parameter is sensitive within all models at the Tucson site.

5.3.2. Models With Similar Structure

[55] Because BATS 2 constitutes a development of BATS 1e by modification of the vegetation module, all of

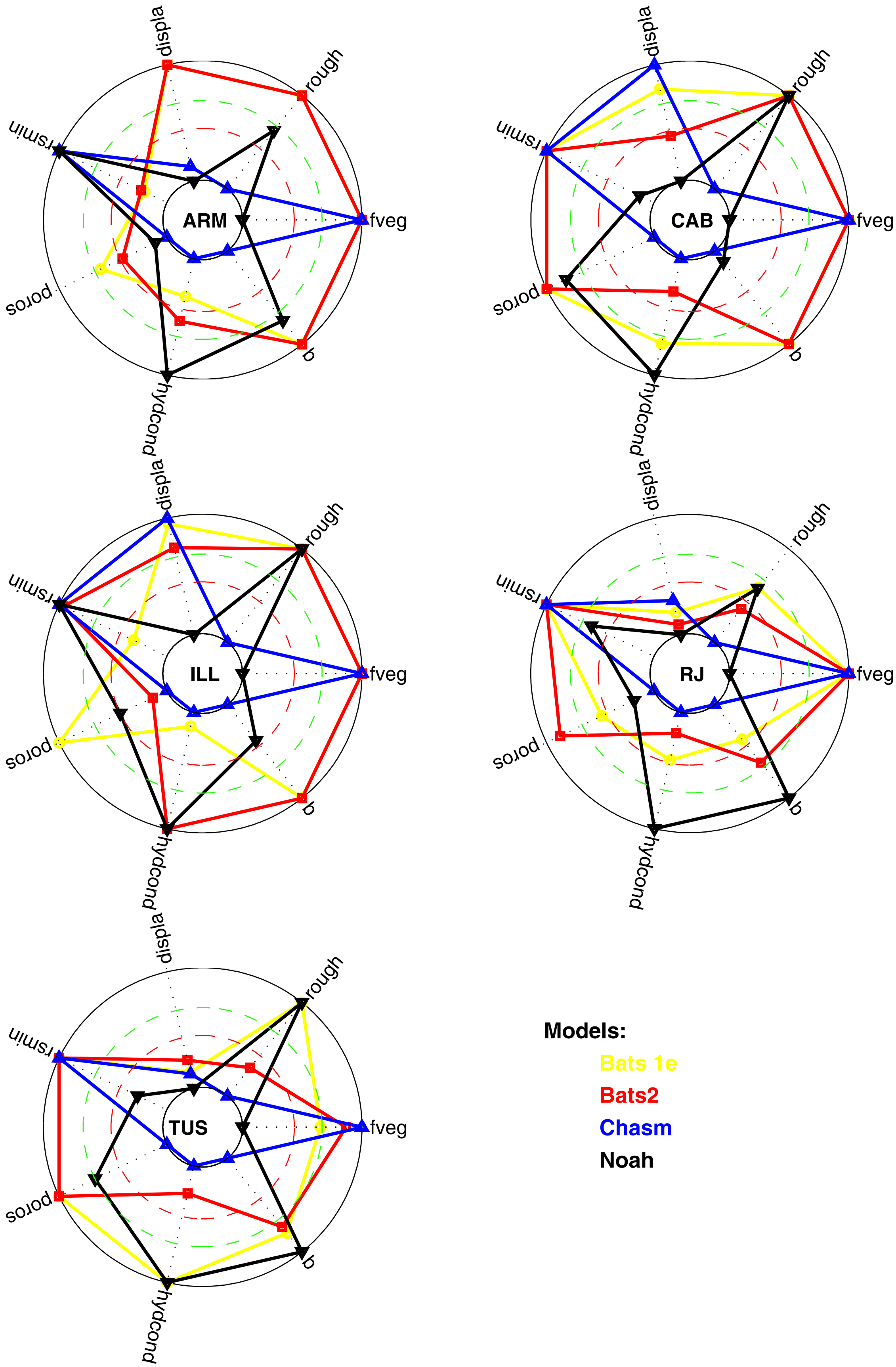
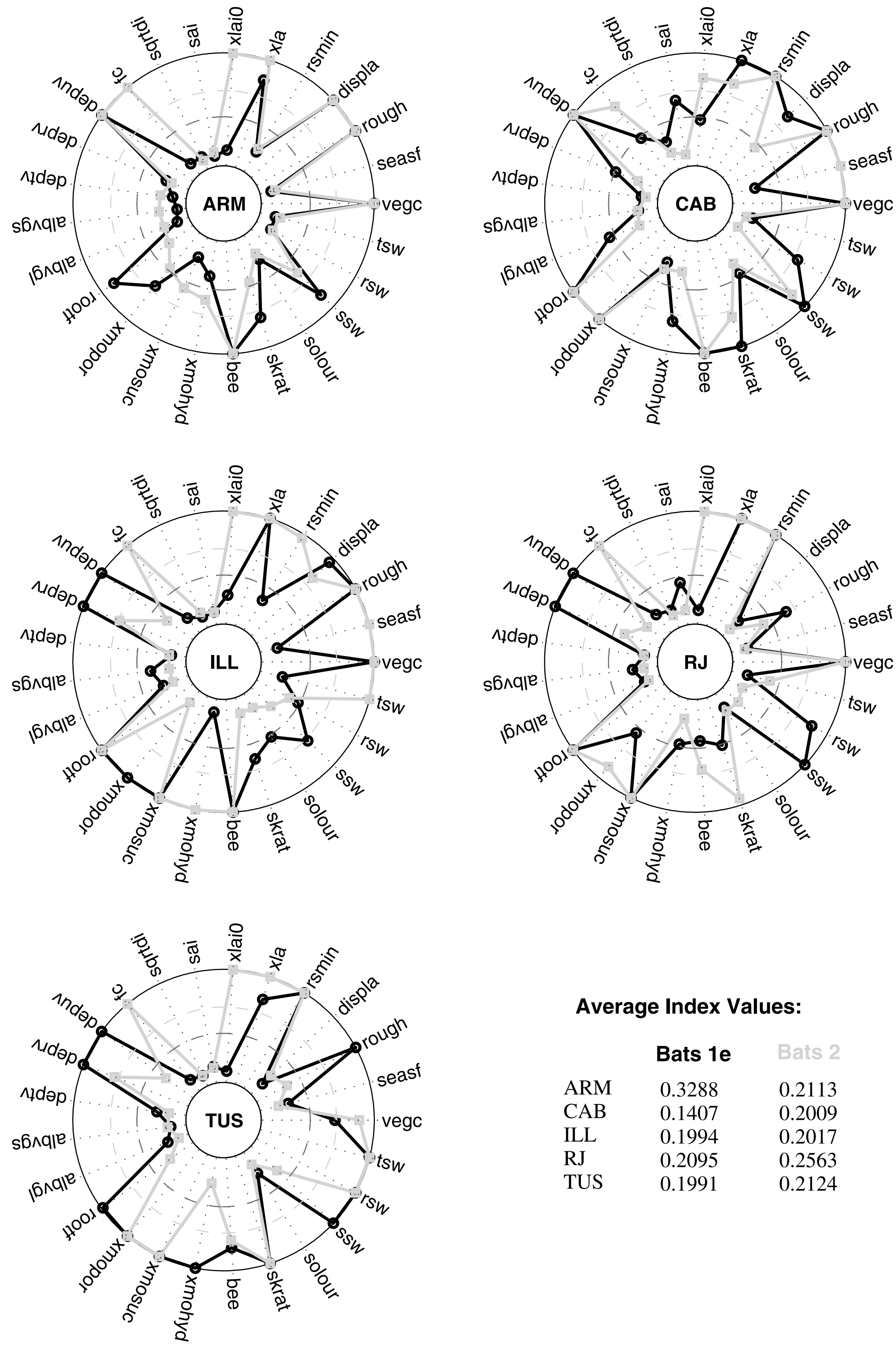


Figure 5. Global multicriteria sensitivity of parameters with similar "physical meaning" across models.



	Bats 1e	Bats 2
ARM	0.3288	0.2113
CAB	0.1407	0.2009
ILL	0.1994	0.2017
RJ	0.2095	0.2563
TUS	0.1991	0.2124

Figure 6. Global multicriteria sensitivity of common parameters between Bats 1 and Bats 2 models.

Table 9. Ranking of Global Sensitivity Indices at Different Sites for the BATS 1e and BATS 2 Models[a]

	Sensitive Parameters									
	ARMCART		Cabauw		Illinois		Reserva Jaru		Tucson	
					BATS 1e					
1	vegc	0.0000	vegc	0.0000	vegc	0.0000	vegc	0.0000	rough	0.0000
2	rough	0.0000	rough	0.0000	rough	0.0000	rsmin	0.0000	depuv	0.0000
3	displa	0.0000	rsmin	0.0000	xla	0.0000	xla	0.0000	deprv	0.0000
4	bee	0.0000	xla	0.0000	deprv	0.0000	depuv	0.0000	xmopor	0.0000
5	depuv	0.0001	depuv	0.0000	rootf	0.0000	deprv	0.0000	xmosuc	0.0000
6	rootf	0.0025	rootf	0.0000	xmosuc	0.0000	rootf	0.0000	xmohyd	0.0000
7	ssw	0.0028	xmopor	0.0000	bee	0.0000	xmosuc	0.0000	skrat	0.0000
8	xla	0.0036	bee	0.0000	xmopor	0.0001	ssw	0.0000	ssw	0.0000
9	skrat	0.0065	skrat	0.0000	depuv	0.0008	rsw	0.0029	tsw	0.0000
10	xmopor	0.0143	ssw	0.0000	displa	0.0014	rough	0.0175	rsmin	0.0003
11			displa	0.0042	ssw	0.0086	xmopor	0.0347	rsw	0.0009
12			xmohyd	0.0064	skrat	0.0195	skrat	0.0466	rootf	0.0011
13			rsw	0.0077	solour	0.0434			bee	0.0040
14			sai	0.0163					xla	0.0043
15			albvgl	0.0357					vegc	0.0110
					BATS 2					
1	vegc	0.0000	vegc	0.0000	vegc	0.0000	vegc	0.0000	rsmin	0.0000
2	rough	0.0000	rough	0.0000	rough	0.0000	xla	0.0000	xla	0.0000
3	displa	0.0000	rsmin	0.0000	xla	0.0000	xlai0	0.0000	xlai0	0.0000
4	xla	0.0000	depuv	0.0000	xlai0	0.0000	fc	0.0000	fc	0.0000
5	xlai0	0.0000	bee	0.0000	fc	0.0000	rootf	0.0000	xmopor	0.0000
6	fc	0.0000	xmopor	0.0002	rootf	0.0000	xmosuc	0.0000	xmosuc	0.0000
7	depuv	0.0000	rootf	0.0003	xmohyd	0.0000	rsmin	0.0002	skrat	0.0000
8	bee	0.0000	seasf	0.0004	bee	0.0000	skrat	0.0015	tsw	0.0000
9	ssw	0.0206	ssw	0.0029	tsw	0.0000	xmopor	0.0024	rsw	0.0002
10	xmohyd	0.0246	xla	0.0045	xmosuc	0.0001	bee	0.0137	vegc	0.0025
11	xmosuc	0.0327	xlai0	0.0045	seasf	0.0008	rough	0.0838	bee	0.0063
12			fc	0.0045	rsmin	0.0013	tsw	0.0880	deprv	0.0077
13			skrat	0.0067	displa	0.0057	deprv	0.0962		
14					deprv	0.0107				

[a]The number of sensitive parameters may differ from those in Table 7 because of the initial states inclusion.

the BATS 1e parameters appear in the BATS 2 model, and we can safely assume that the parameters common to these models (25 in total) are intended to have the same physical meaning. On the other hand, in the previous analysis the use of the K-S probability value as a sensitivity index is only justified as a proxy, because of the differences in model structure –different parameterizations, and different types of parameter interactions. We can also include the analysis of the initial soil moisture conditions for both models because the soil submodel is essentially the same.

[56] A graphical summary of the global sensitivity, at the five different sites, for the common 22 parameters and 3 initial conditions at the five sites is presented in Figure 6. The actual values of the sensitivity indices (the median of the Kolomogorov-Smirnov statistic) and the ranking of the sensitivity levels are presented in Table 9. The most interesting difference between the models is in the behavior of the initial soil moisture content and the depths of the soil layers, despite the fact that the soil submodel structure is basically the same.

[57] Of the parameters related to the vegetation model the vegetation fraction (*vegc*) is highly sensitive for both models at all the sites. The same occurs with the roughness length except for the BATS 2 at the Tucson site. The leaf area index (*xla*) and the Clapp and Hornberger '*b*' are also very sensitive for both models at all sites. The root fraction (*rootf*) is sensitive at all sites for the BATS 1 but is not sensitive for the BATS 2 at the ARMCART and Tucson sites. Those two sites, interestingly, are the ones with higher moisture constraints. The vegetation and soil albedos are not sensitive. Thus it can be said that the sensitivity behavior of the vegetation submodel parameters is similar in the two models, despite the fact that the vegetation submodel is the one with the main changes in structure.

[58] The picture is different with the soil-related parameters where the behavior of the parameter sensitivity varies significantly from site to site within the two different models. Porosity (*xmopor*) is the most sensitive parameter. It is sensitive at all the sites with the BATS 1 and only at Cabauw, Reserva Jaru, and Tucson for the BATS 2. Hydraulic conductivity (*xmohyd)* is only sensitive at two sites (although different ones) for both models. The soil suction (*xmosuc*) is sensitive at all sites except Cabauw for the BATS 2, while is not sensitive for Cabauw and the ARMCART in the BATS 1. The parameter related to the thermal conductivity of the soil (*skrat*) is sensitive for all sites within BATS 1, but is only sensitive for the Tucson site in BATS 2. The thickness of the upper soil layer is also very sensitive across all sites in BATS 1, while only at ARMCART and Cabauw in BATS 2. The depth of the root layer (*deprv*) is sensitive for both models at the Illinois, Reserva Jaru, and Tucson sites. Associated with the soil are also the initial moisture states for the three soil layers. The most sensitive state is the upper layer water content (*ssw*) which is sensitive at all sites for the BATS 1 while only sensitive at the ARMCART and Cabauw for the BATS 2. The root zone initial water content (*rsw*) is again more sensitive for the BATS 1, with three sites, while only sensitive at one (Tucson) for BATS 2.

[59] In summary it can be said that, paradoxically, the behavior of the soil-related parameters appears to be more affected by changes in the vegetation parameterization than the actual vegetation-related parameters. This is mostly associated with the sensitivity to the latent heat.

6. Summary, Conclusions, and Recommendations

[60] A comparison of land surface model sensitivity has been carried out within a multicriteria framework. To carry out the comparison, a large number (~50,000) of model runs were made. The total number of model parameters was used as a proxy for the level of model complexity. The BATS 2 model is the model with the highest complexity in terms of process representation. The analysis reveals that relationship between level of complexity and overall sensitivity is not straightforward. It is clear that sensitivity is a function of location, which in the present case is associated with the forcing variables. When evaluating the number of sensitive parameters for the models studied, Noah has the highest sensitivity (largest index), which means the parameter interaction is less acute, but is not the model with highest model complexity. The BUCKET model, although contains no explicit vegetation parameters, does have sensitivity to its soil parameters at the more humid sites in the study (Cabauw and Reserva Jaru). The CHASM model also has a fair number of sensitive parameters for the level of complexity. BATS2, which includes the more advanced vegetation parameterization than either the BATS1e or Noah models, does not necessarily result in a higher number of sensitive parameters, even for its vegetation parameters. The increasing complexity of the BATS2 model over the BATS1e does not necessarily result in a larger number of identifiable parameters. In fact, the additional complexity in the BATS2 model may be causing interaction among the parameters and fewer sensitive parameters. The Noah model (used in operational weather forecasting) tends to lean more toward soil sensitivity rather than sensitivity to vegetation parameters.

[61] The analysis also revealed that several model parameters appear to be insensitive regardless of the input data. This conclusion indicates a reduction in the number of parameters a modeler need be concerned with at any site, and will aid in the development of a systematic approach for defining sensitive and nonsensitive parameters and estimating those variables which truly influence model simulations.

[62] The analysis also showed that the sensitivity of parameters with similar physical meaning is tightly related to the model structure and location. If a particular parameter is sensitive for a specific model and location, it does not necessarily follows that the parameter will be sensitive at a different location, and for a different model.

[63] The added complexity in the vegetation submodel of the BATS 2, with respect to BATS 1, paradoxically produces bigger changes in soil-related parameters than in vegetation-related ones. The sensitivity to initial moisture states in the soil is also affected by the change in the vegetation representation.

[64] Because streamflow was not used as a criterion or variable in this analysis, few conclusions can be drawn on the sensitivity of the runoff processes. It is expected this result may change if streamflow or runoff data were used as a criterion in a sensitivity analysis.

[65] Results from this sensitivity analysis demonstrate that the MOGSA procedure provides a useful framework that takes into account parameter interaction and allows for multicriteria and single-criterion analysis, irrespective of the model structure and number of parameters. This work also supports the concept that there are tradeoffs in model complexity and that the appropriate level of model complexity should be evaluated for a specific combination of vegetation and soil types. In a complementary study, *Hogue et al.* [2005] have applied the current results to reduce the ‘‘curse of dimensionality’’ in the parameter identification problem; that is, only the sensitive parameters have been optimized.

[66] **Acknowledgments.** Primary support for this study was provided by NOAA grant NA86GP0324, NASA-EOS grant NAG5-3640-5, SAHRA (Sustainability of Semi-Arid Hydrology and Riparian Areas) under the STC Program of the National Science Foundation Agreement EAR-9876800, and the Utah Water Research Laboratory. Additional support came from NASA grant NAG8-1531. W. J. Shuttleworth's contribution to this study was supported by NASA grant NCC5-709. Special thanks are due to Robert E. Dickinson, Andy Pitman, and Adam Schlosser for providing the BATS2, CHASM, and BUCKET computer codes. TheReserva Jaru data were collected under the ABRACOS project and were made available by the U.K. Institute of Hydrology and the Instituto Nacional de Pesquisas Espaciais (Brazil). The NSA-OJP tower flux data were provided by David R. Fitzjarrald and Kathleen E. Moore. Their contributions to providing these data sets are greatly appreciated. We acknowledge the Royal Netherlands Meteorological Institute for providing the Cabauw data. Special thanks are due to Helene Unland for providing the Tucson data set and to Jim Washburne for providing the ARM-CART data set.

References

Ball, J. T., I. E. Woodrow, and J. A. Berry (1987), A model predicting stomatal conductance and its contribution to the control of photosynthesis under different environmental conditions, in *Progress in Photosynthesis Research*, vol. 1, edited by J. Biggins, pp. 221–234, Martinus Nijhof, Zoetermeer, Netherlands.

Bastidas, L. A. (1998), Parameter estimation for hydrometeorological models using multi-criteria methods, Ph. D. diss., Dep. of Hydrol. and Water Resour., Univ. of Ariz., Tucson.

Bastidas, L. A., H. V. Gupta, S. Sorooshian, W. J. Shuttleworth, and Z. L. Yang (1999), Sensitivity analysis of a land surface scheme using multicriteria methods, *J. Geophys. Res.*, *104*, 19,481–19,490.

Beck, M. B. (2002), Introduction, in *Environmental Foresight and Models: A Manifesto*, edited by M. B. Beck, pp. 3–9, Elsevier, New York.

Beljaars, A. C., and F. C. Bosveld (1997), Cabauw data for the validation of land surface parameterization schemes, *J. Clim.*, *10*, 1172–1193.

Boone, A., F. Habets, and J. Noilhan (2001), The Rhone-AGGregation Experiment, *GEWEX News*, *11*, 3–5.

Braud, I., A. C. Dantas-Antonino, M. Vauclin, J. L. Thony, and P. Ruelle (1995), A Simple Soil-Plant-Atmosphere Transfer Model (SiSPAT) development and field verification, *J. Hydrol.*, *166*, 213–250.

Budyko, M. I. (1956), *The Heat Balance of the Earth's Surface*, 255 pp., Gidrometeoizdat, St. Petersburg, Russia.

Chen, T. H., et al. (1997), Cabauw experimental results from the Project for Intercomparison of Land Surface Parameterisation Schemes (PILPS), *J. Clim.*, *10*, 1194–1215.

Collins, D. C., and R. Avisssar (1994), An evaluation with the Fourier amplitude sensitivity test (FAST) of which land surface parameters are of greatest importance in atmospheric modeling, *J. Clim.*, *7*, 681–703.

Deardoff, J. W. (1978), Efficient prediction of groundwater temperature and moisture, with inclusion of a layer of vegetation, *J. Geophys. Res.*, *83*, 1889–1903.

Demarty, J., C. Ottlé, I. Braud, J. P. Frangi, L. A. Bastidas, and H. V. Gupta (2004), Using a multi-objective sensitivity analysis to calibrate the SiSPAT-RS model, *J. Hydrol.*, *287*, 214–236.

Desborough, C. (1999), Surface energy balance complexity in GCM land surface models, *Clim. Dyn.*, *15*, 389–403.

Dickinson, R. E., A. Henderson-Sellers, and P. J. Kennedy (1993), Biosphere Atmosphere Transfer Scheme (BATS) version 1e as coupled to the NCAR Community Climate Model, *NCAR Tech. Note NCAR/TN-387+STR*, 72 pp., Natl. Cent. for Atmos. Res., Boulder, Colo.

Dickinson, R. E., M. Shaick, R. Bryant, and L. Graumlich (1998), Interactive canopies for a climate model, *J. Clim.*, *11*, 2823–2836.
Driese, K. L., and W. A. Reiners (1997), Aerodynamic roughness parameters for semi-arid natural shrub communities of Wyoming, USA, *Agric. For. Meteorol.*, *88*, 1–14.
Efron, B. (1979a), Bootstrap methods: Another look at the jackknife, *Ann. Stat.*, *7*, 1–26.
Efron, B. (1979b), Computers and the theory of statistics: Thinking the unthinkable, *Soc. Ind. Appl. Math.*, *21*, 460–480.
Ek, M. B., K. E. Mitchell, Y. Lin, P. Grunmann, E. Rogers, G. Gayno, and V. Koren (2003), Implementation of the upgraded Noah land-surface model in the NCEP operational mesoscale Eta model, *J. Geophys. Res.*, *108*(D22), 8851, doi:10.1029/2002JD003296.
Farquhar, G. D., S. von Caemmerer, and J. A. Berry (1980), A biochemical model of photosynthetic CO_2 assimilation in leaves of C3 plants, *Planta*, *147*, 78–90.
Franks, S. W., and K. J. Beven (1997), Bayesian estimation of uncertainty in land-surface-atmosphere flux predictions, *J. Geophys. Res.*, *102*, 23,991–23,999.
Gao, X., S. Sorooshian, and H. V. Gupta (1996), Sensitivity analysis of the Biosphere-Atmosphere Transfer Scheme, *J. Geophys. Res.*, *101*, 7279–7289.
Goldberg, D. E. (1989), *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley, Boston, Mass.
Gupta, H. V., S. Sorooshian, and P. O. Yapo (1998), Towards improved calibration of hydrologic models: Multiple and non-commensurable measures of information, *Water Resour. Res.*, *34*, 751–763.
Gupta, H. V., L. A. Bastidas, S. Sorooshian, W. J. Shuttleworth, and Z. L. Yang (1999), Parameter estimation of a land surface scheme using multicriteria methods, *J. Geophys. Res.*, *104*, 19,491–19,504.
Gutman, G., and A. Ignatov (1998), The derivation of the green vegetation fraction from NOAA/AVHRR data for use in numerical weather prediction models, *Int. J. Remote Sens.*, *19*, 1533–1543.
Henderson-Sellers, A., and V. B. Brown (1992), Project for Intercomparison of Landsurface Parameterization Schemes (PILPS): First science plan, *IGPO Publ. Ser. 5*, 53 pp., Int. Global Energy and Water Cycle Program Proj. Off., Silver Spring, Md.
Henderson-Sellers, A., A. J. Pitman, P. K. Love, P. Irannejad, and T. H. Chen (1995), The Project for Intercomparison of Land Surface Parameterization Schemes (PILPS): Phases 2 and 3, *Bull. Am. Meteorol. Soc.*, *76*, 489–503.
Hodnett, M. G., L. P. da Silva, H. R. da Rocha, and R. C. Cruz Senna (1995), Seasonal soil water storage changes beneath central Amazonian rainforest and pasture, *J. Hydrol.*, *170*, 233–254.
Hogue, T. S., L. A. Bastidas, H. Gupta, S. Sorooshian, K. Mitchell, and W. Emmerich (2005), Evaluation and transferability of the Noah land surface model in semiarid environments, *J. Hydrometeorol.*, *6*, 68–84.
Hogue, T. S., L. A. Bastidas, H. V. Gupta, and S. Sorooshian (2006), Evaluating model performance and parameter behavior for varying levels of land surface model complexity, *Water Resour. Res.*, *42*, W08430, doi:10.1029/2005WR004440.
Hornberger, G. M., and R. C. Spear (1981), An approach to the preliminary analysis of environmental systems, *J. Environ. Manage.*, *12*, 7–18.
Hornberger, G. M., K. J. Beven, B. J. Cosby, and D. E. Sappington (1985), Shenandoah watershed study: Calibration of a topography-based, variable contributing area hydrological model to a small forested catchment, *Water Resour. Res.*, *21*, 1841–1850.
Koster, R. D., and M. J. Suarez (1992), Modeling the land surface boundary in climate models as a composite of independent vegetation stands, *J. Geophys. Res.*, *97*, 2697–2719.
Lettenmaier, D., D. Lohmann, E. F. Wood, and X. Liang (1996), PILPS-2c workshop report, Princeton Univ., Princeton, N. J.
Liang, X., and J. Guo (2003), Intercomparison of land-surface parameterization schemes: Sensitivity of surface energy and water fluxes to model parameters, *J. Hydrol.*, *279*, 182–209.
Mahrt, L., and H. Pan (1984), A two-layer model of soil hydrology, *Boundary Layer Meteorol.*, *23*, 1–20.
Manabe, S. (1969), Climate and the ocean circulation. I. The atmospheric circulation and the hydrology of the Earth's surface, *Mon. Weather Rev.*, *97*, 739–774.
Mitchell, K., et al. (2000), Recent GCIP-sponsored advancements in coupled land-surface modeling and data assimilation in the NCEP ETA mesoscale model, paper presented at 15th Conference on Hydrology, Am. Meteorol. Soc., Long Beach, Calif.
Mitchell, K. E., et al. (2004), The multi-institution North American Land Data Assimilation System (NLDAS) project: Utilizing multiple GCIP products and partners in a continental distributed hydrological modeling system, *J. Geophys. Res.*, *109*, D07S90, doi:10.1029/2003JD003823.
Nijssen, B., et al. (2003), Simulation of high latitude hydrological processes in the Torne-Kalix basin: PILPS phase 2(e) 2: Comparison of model results with observations, *Global Planet. Change*, *38*, 31–53.
Pitman, A. J. (1994), Assessing the sensitivity of a land-surface scheme to the parameter values using a single column model, *J. Clim.*, *7*, 1856–1869.
Pitman, A. J. (2003), Review: The evolution of, and revolution in, land surface schemes designed for climate models, *Int. J. Climatol.*, *23*, 479–510.
Pitman, A. J., and A. Henderson-Sellers (1998), Recent progress and results from the Project for the Intercomparison of Landsurface Parameterization Schemes, *J. Hydrol.*, *212*, 128–135.
Pitman, A. J., et al. (1999), Key results and implications from phase 1(c) of the Project for Intercomparison of Land-Surface Parameterization Schemes, *Clim. Dyn.*, *15*, 673–684.
Rabitz, H. (1989), System analysis at molecular scale, *Science*, *246*, 221–226.
Rabitz, H., and O. Alis (2000), Managing the tyranny of parameters in mathematical modeling of physical systems, in *Sensitivity Analysis*, edited by A. Saltelli, K. Chan, and E. M. Scott, pp. 199–224, John Wiley, Hoboken, N. J.
Robock, A., K. Y. Vinnikov, C. A. Schlosser, N. A. Speranskaya, and Y. Xue (1995), Use of midlatitude soil moisture and meteorological observations to validate soil moisture simulations with biosphere and bucket models, *J. Clim.*, *8*, 15–35.
Rousseeuw, P. J. (1991), Tutorial to robust statistics, *Chemometrics, J.*, *5*, 1–20.
Saltelli, A. (1999), Sensitivity analysis: Could better methods be used?, *J. Geophys. Res.*, *104*, 3789–3793.
Saltelli, A. (2000), What is sensitivity analysis?, in *Sensitivity Analysis*, edited by A. Saltelli, K. Chan, and E. M. Scott, pp. 3–13, John Wiley, Hoboken, N. J.
Schlosser, C. A., A. Robock, K. Y. Vinnikov, N. A. Speranskaya, and Y. Xue (1997), 18–year land-surface hydrology model simulations for a midlatitude grassland catchment in Valdai, Russia, *Mon. Weather Rev.*, *125*, 3279–3296.
Schlosser, C. A., et al. (2000), Simulations of a boreal grassland hydrology at Valdai, Russia: PILPS phase 2(d), *Mon. Weather Rev.*, *128*, 301–321.
Sen, O. L., L. A. Bastidas, W. J. Shuttleworth, Z. L. Yang, H. V. Gupta, and S. Sorooshian (2001), Impact of field calibrated vegetation parameters on GCM Climate simulations, *Q. J. R. Meteorol. Soc.*, *127*, 1199–1224.
Sorooshian, S., and V. K. Gupta (1995), Model calibration, in *Computer Models of Watershed Hydrology*, edited by V. P. Singh, pp. 23–68, Water Resour. Publ., Highlands Ranch, Colo.
Spear, R. C., and G. M. Hornberger (1980), Eutrophication in peel inlet, II, Identification of critical uncertainties via generalized sensitivity analysis, *Water Res.*, *14*, 43–49.
Spear, R. C., T. M. Grieb, and N. Shang (1994), Parameter uncertainty and interaction in complex environmental models, *Water Resour. Res.*, *30*, 3159–3169.
Unland, H. E., P. R. Houser, W. J. Shuttleworth, and Z.-L. Yang (1996), Surface flux measurement and modeling at a semi-arid Sonoran Desert site, *Agric. Forest Meteorol.*, *82*, 119–153.
Viterbo, P. (2002), *A Review of Parametrization Schemes for Land Surface Processes*, *Meteorol. Training Course Lecture Ser.*, 49 pp., Eur. Cent. for Med.-Range Weather Forecasts, Reading, U.K.
Wilson, M. F., A. Henderson-Sellers, R. E. Dickinson, and P. J. Kennedy (1987a), Sensitivity of the Biosphere Atmosphere Transfer Scheme (BATS) to the inclusion of variable soil characteristics, *J. Climatol. Appl. Meteorol.*, *26*, 341–362.
Wilson, M. F., A. Henderson-Sellers, R. E. Dickinson, and P. J. Kennedy (1987b), Investigation of the sensitivity of the land surface parameterization of the NCAR Community Climate Model in regions of tundra vegetation, *Climatol.*, *7*, 319–343.

L. A. Bastidas, Department of Civil and Environmental Engineering and Utah Water Research Laboratory, Utah State University, 8200 Old Main Hill, Logan, UT 84322-8200, USA. (luis.bastidas@usu.edu)

H. V. Gupta, Department of Hydrology and Water Resources, University of Arizona, Tucson, AZ 85721, USA.

T. S. Hogue, Department of Civil and Environmental Engineering, University of California, Los Angeles, 5732C Boelter Hall, Los Angeles, CA 90095-1593, USA.

W. J. Shuttleworth, SAHRA, Marshall Building, Room 530, 845 N. Park Avenue, Building 158-B, 5th Floor, P.O. Box 210158-B, Tucson, AZ 85721-0158, USA.

S. Sorooshian, CHRS, Department of Civil and Environmental Engineering, University of California, Irvine, E-4130 Engineering Gateway, Irvine, CA 92697-2175, USA.